International Journal of Instruction *July 2026 ● Vol.19, No.3*
e-ISSN: 1308-1470 ● www.e-iji.net *p-ISSN: 1694-609X*
pp. 479-502

Article submission code: 20251021024938
Received: 21/10/2025
Revision: 04/02/2026
Accepted: 15/02/2026
OnlineFirst: 05/04/2026

Teachers' Behavioral Intention Toward Using Generative Artificial Intelligence (GAI): The Role of TPACK and Self-Efficacy

Guohua Wang
Department of Education, Henan Normal University, China, *wgh19892008@126.com*

Xueru Xing
Department of Education, Henan Normal University, China, *xingxr2001@163.com*

Fang Zhang
Department of Education, Henan Normal University, China, *303039627@qq.com*

Generative Artificial Intelligence (GAI), representing a new phase in AI development, is profoundly transforming the field of education, presenting novel opportunities for educational innovation and reform. This study aimed to investigate the key predictors of the behavioral intentions of primary and secondary school teachers in adopting GAI for instructional support. A combination of convenience sampling and snowball sampling was employed to collect questionnaire data from 561 K-12 teachers across multiple provinces in China. Based on the Technology Acceptance Model (TAM) and integrating core variables such as teachers' Technological Pedagogical and Content Knowledge (TPACK) and self-efficacy, the data were analyzed using structural equation modeling.The results indicated that teachers' TPACK, self-efficacy, and perceived usefulness of GAI all significantly and positively predicted their behavioral intention to use it. However, no direct correlation was found between perceived ease of use and behavioral intention. This study provides new empirical evidence for understanding teachers' acceptance mechanisms toward intelligent educational technology and offers practical implications for designing more targeted teacher professional development programs. The conclusions of this study are limited by its cross-sectional design and specific sample scope; future research could employ longitudinal designs and broader sampling to verify and deepen these findings.

Keywords: generative artificial intelligence, TAM, TPACK, self-efficacy, K-12 teachers, behavioral intention

INTRODUCTION

Generative Artificial Intelligence (GAI), as a key technology driving educational innovation and transformation, is reshaping the educational ecosystem through human-machine collaboration and personalized learning (Sun et al., 2024). However, while offering new opportunities for education, it also presents significant challenges for teachers (Kaplan-Rakowski et al., 2023). Research indicates that teachers may harbor

Citation: Wang, G., Xing, X., & Zhang, F. (2026). Teachers' behavioral intention toward using generative artificial intelligence (GAI): The role of TPACK and self-efficacy. *International Journal of Instruction*, *19*(3), 479-502.

skepticism or hesitation towards GAI due to its technical complexity, their own insufficient preparedness, and concerns regarding ethical risks (Herodotou et al., 2019), which directly hinders its effective integration into teaching practice.

Among the key factors influencing teachers' technology acceptance, Technological Pedagogical and Content Knowledge (TPACK) and self-efficacy have received extensive attention (Bao et al., 2021; Qiu et al., 2022). As self-efficacy is domain-specific (Bandura, 1977), this study focuses specifically on GAI-related self-efficacy—defined as teachers' confidence in their ability to effectively use GAI tools to accomplish specific teaching tasks—to precisely capture the psychological mechanisms at play when teachers engage with this emerging technology.

Although the predictive roles of TPACK and self-efficacy in general technology adoption are well-established, empirical research specifically on K-12 teachers' adoption of GAI remains in its nascent stages, with limited studies and explanatory power (Chiu et al., 2020). Existing research has often inadequately addressed the unique contextual constraints of K-12 education, such as the common practical dilemma of "high device access yet low adoption rates", and the additional ethical burden placed on teachers by stringent data privacy regulations concerning minors (Ng et al., 2022). These distinct real-world factors create a complex decision-making environment, suggesting that generic technology acceptance models may have limitations in directly explaining the GAI adoption behaviors of K-12 teachers.

Building on prior research, this study proposes and tests an integrated explanatory model for GAI adoption by K-12 teachers. Aiming to address the dual gaps in contextual depth and variable specificity in current literature, the model's core innovation lies in its systematic integration of two key variables: domain-specific knowledge (TPACK) and technology-specific self-efficacy (GAI self-efficacy). It empirically investigates how these variables, under the complex constraints inherent to basic education, jointly influence teachers' behavioral intentions through the mediating pathways of "perceived usefulness" and "perceived ease of use." This provides a more precise and practice-aligned theoretical lens for understanding the complex decision-making mechanisms of teachers facing this emerging technology.

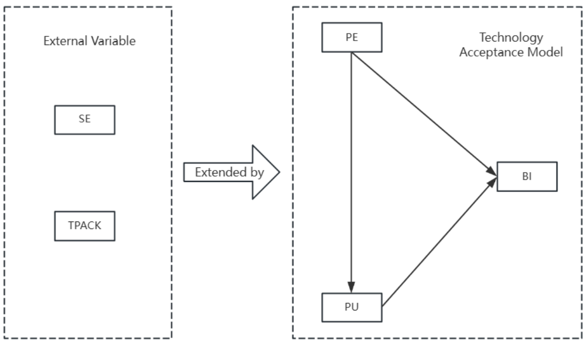

Figure 1
An extended model based on TAM

OVERVIEW

GAI in Education

Artificial Intelligence is regarded as an integration of science, engineering, and mathematics, capable of mimicking and executing human cognitive functions such as judgment, reasoning, learning, and problem-solving (Gao et al., 2019). It holds significant potential to advance educational development and transformation (Shen et al., 2023). Since the launch of ChatGPT, Generative Artificial Intelligence (GAI), with its powerful content generation and interactive capabilities, has rapidly emerged as a key technological driver in education. At the practical level, GAI can analyze student learning data and behavioral patterns to provide highly personalized learning support and resource adaptation (Shen et al., 2023). It can also generate instructional materials aligned with teaching objectives to foster student cognitive development (Wang et al., 2024). Furthermore, GAI assists in automating teaching processes, supporting lesson planning, academic assessment, and teacher professional development, thereby significantly reducing teachers' workload while enhancing teaching efficiency and quality (Li et al., 2024). Additionally, GAI is increasingly being applied in educational management and learning analytics. It can help handle administrative tasks (Ahmad et al., 2022) and provide data support for educational decision-making, promoting a shift towards more scientific and intelligent educational governance (Ke et al., 2024; Demartini et al., 2024). Thus, GAI is reshaping the educational ecosystem across multiple dimensions, offering systemic support for teaching, management, and decision-making.

Behavioral Intention for GAI Integration into Teaching Practice

Behavioral Intention (BI) is a key variable for predicting an individual's actual technology adoption and use, commonly defined as "the degree to which an individual plans to use a specific technology in the future" (Davis, 1989). Within the context of AI in education, this study defines teachers' behavioral intention to integrate GAI into teaching practice as their willingness and preparedness to adopt and use GAI in future instruction. Teachers' intention to use AI in teaching is crucial for enhancing pedagogical efficiency and quality .

Existing research exploring teachers' behavioral intentions in authentic teaching contexts has identified several influential factors (Lee et al., 2023). Among these, self-efficacy and perceived usefulness have been confirmed to have a positive and significant impact on behavioral intention (Kumar et al., 2020). A deeper understanding of these factors aids in developing more targeted strategies and interventions to promote teachers' willingness to integrate AI into teaching (Joo et al., 2018). For instance, Gurer (2021) investigated the formation mechanism of teachers' behavioral intention to use AI technology from dimensions including attitude, thereby broadening the research perspective in this area.

Factors Influencing Teachers' Willingness to Incorporate GAI into Teaching Practice

The Technology Acceptance Model (TAM) is a classic theoretical framework for explaining and predicting users' technology acceptance behavior. It posits that perceived usefulness and perceived ease of use are the core cognitive factors influencing an individual's adoption intention. Specifically, perceived usefulness refers to the degree to which a teacher believes that using a particular technology can enhance their teaching effectiveness, achieve pedagogical goals, or improve work efficiency. Perceived ease of use denotes the degree to which a teacher perceives that learning and using the technology requires minimal effort (Shodipe et al., 2020). Previous research has confirmed that these two perceptions significantly influence teachers' behavioral intention regarding technology use (Hong et al., 2021). Based on this, the present study hypothesizes: Perceived Usefulness (PU) and Perceived Ease of Use (PE) have a direct and significantly positive influence on teachers' behavioral intention (BI) to integrate GAI into teaching practice.

Beyond these cognitive factors, teachers' professional knowledge structure and psychological motivation also play crucial roles in the technology adoption process. Technological Pedagogical and Content Knowledge (TPACK) serves as the professional knowledge framework for teachers to effectively conduct technology-integrated instruction, encompassing the interaction and integration among technology, pedagogy, and subject content (Li et al., 2024). Research indicates that teachers with higher levels of TPACK not only perceive technology as more useful and easier to use (Yang et al., 2021) but are also more capable of integrating new technologies like GAI with specific teaching contexts (Bai et al., 2024). Simultaneously, self-efficacy, reflecting teachers' confidence in their ability to use GAI technology, has also been shown to positively predict their actual use of GAI (Xu et al., 2021). Therefore, this study further hypothesizes that TPACK and self-efficacy (SE) not only directly influence teachers' behavioral intention (BI) to use GAI but also exert an indirect influence by enhancing their perceived usefulness (PU) and perceived ease of use (PE).

In conclusion, TPACK, SE, PU, and PE are key factors that influence BI among K12 teachers. Understanding these factors and their interrelationships is the basis for developing strategies and interventions aimed at increasing K12 teachers' readiness and motivation to effectively incorporate AI technologies into their teaching practices.

Theoretical Framework and Assumptions

Theoretical Framework

The Technology Acceptance Model (TAM), initially conceptualized by Davis, serves as a framework for gauging the acceptance of information technology systems by users. Initially, TAM encompassed four key variables: perceived usefulness, perceived ease of use, attitude toward use, and behavioral intention to use (Davis, 1989). Within this framework, perceived usefulness and perceived ease of use were recognized as the central determinants of technology acceptance. To address the initial constraints of the model, Venkatesh and Davis (2000) integrated additional external variables into TAM that impact perceived usefulness, perceived ease of use, and the intention to utilize technology. This research, after reviewing relevant literature, determines that TPACK and SE are among the external factors that influence educators' adoption of GAI.

Hypotheses

Drawing from the research context provided, the objective of this inquiry is to assess the current landscape and the readiness of educators in middle and high schools to incorporate GAI into their instructional strategies. The study utilized a survey called the "Teachers' Use of GAI in Teaching and Learning Scale" to measure and quantify the propensity of middle and high school educators to adopt GAI in their teaching methodologies. In addition, the study sought to analyze in depth the interconnections between this willingness and a range of influencing factors, revealing potential causal relationships. Specifically, the following research questions were answered:

1 · To what extent do TPACK, SE, PE, and PU significantly influence BI in the instructional practices of primary and secondary teachers?

2 · How are the influences of TPACK, SE, PE, and PU among elementary and secondary teachers interrelated?

To answer these research questions, the study formulated the following research hypotheses regarding the mechanism of influence between the independent and dependent variables (Figure 2).

H1: SE significantly and directly affects the BI of educators at the K-12 level concerning the implementation of GAI-assisted instruction.

H2: TPACK significantly and directly affects the BI of educators at the K-12 level concerning the implementation of GAI-assisted instruction.

H3: TPACK significantly influences the BI of educators at the K-12 level concerning the implementation of GAI-assisted instruction through PU.

H4: SE significantly influences the BI of educators at the K-12 level concerning the implementation of GAI-assisted instruction through PE.

H5: SE through PU significantly affects the BI of educators at the K-12 level concerning the implementation of GAI-assisted instruction.

H6: SE significantly influences the BI of educators at the K-12 level concerning the implementation of GAI-assisted instruction through PE and PU.

H7: TPACK significantly influences the BI of educators at the K-12 level concerning the implementation of GAI-assisted instruction through PE.

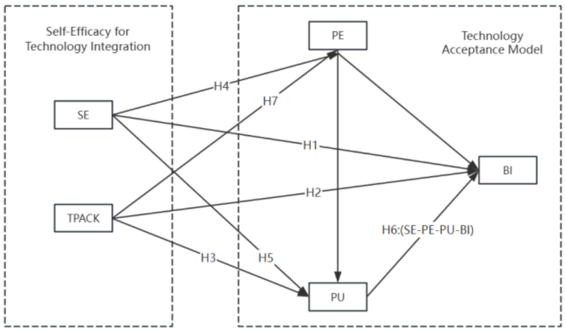

Figure 2
Research hypothesis

METHOD

Background and Participants of Research

To ensure sample diversity and accessibility, this study employed a combination of convenience sampling and snowball sampling to recruit in-service K-12 teachers. Given that teachers at different career stages may vary in their acceptance and use strategies for new technologies, and that teachers from different disciplinary backgrounds may have distinct understandings and needs regarding GAI applications, we consciously aimed to cover a wide range of teaching experience and subject areas during questionnaire design and recruitment. Participants were primarily recruited through: (1) the researchers' personal and professional networks (e.g., recommendations from supervisors and peers), and (2) referrals from initial participants who recommended other eligible teachers.

The final sample included teachers from multiple provinces in Eastern, Central, and Western China. Their teaching experience ranged from 0-3 years to over 20 years, and their teaching subjects covered humanities and social sciences, science and engineering, as well as arts and physical education. This diversity in key demographic variables, while not guaranteeing statistical generalizability to the entire population, enhances the sample's representativeness of the broader teacher community and supports the transferability of the findings to similar educational contexts.

This study received approval from the university ethics committee. Prior to data collection, all potential participants were clearly informed about the research purpose, the voluntary nature of participation, data confidentiality measures, and the provision of a small monetary incentive upon questionnaire completion. The questionnaire could only be accessed after all informed consent terms were confirmed.

The questionnaire was uploaded to the online survey platform "Questionnaire Star" to invite K-12 teachers to participate. A total of 804 initial responses were obtained. Based on predetermined data quality screening criteria, invalid responses were removed. These primarily included cases with a completion time of less than 50 seconds, cases where all items were answered with the same option, and cases identified as outliers during analysis. Consequently, 561 valid questionnaires were retained for subsequent analysis. Within the valid sample, 28.7% were male and 71.3% were female. Table 1 details the demographic characteristics of the final valid participants in the data collection process.

Table 1
Descriptive statistics of samples' demographic information.

Variables	Frequency	Percentage
Gender		
Male	161	28.70
Female	400	71.30
Teaching experience		
<3	70	12.48
3-5	85	15.15
6-10	106	18.89
11-15	72	12.83
16-20	61	10.87
>20	167	29.77
Teaching Subjects		
Literature and History	312	55.61
Science and Engineering	200	35.65
Arts and Sports	49	8.73

Design and Development of a Scale of Teachers' Willingness to Use the GAI to Assist in Teaching

Item Design

The questionnaire consisted of two main sections. The first section collected demographic information from the K-12 teachers, including gender, years of teaching experience, and subject taught. The second section investigated the teachers' behavioral intention, TPACK, perceived usefulness, perceived ease of use, and self-efficacy, employing a five-point Likert scale.

Specifically, the behavioral intention scale was adapted from the frameworks of Ayanwale et al. (2022) and Choi et al. (2022), including items such as "I am willing to use GAI to assist my teaching." The TPACK subscale was developed with reference to and adjustments based on questionnaires by Celik (2023) and Bai et al. (2024), containing items like "I can use GAI tools along with different teaching strategies to deliver a lesson." The perceived usefulness and perceived ease of use subscales were constructed by drawing on the framework of Choi et al. (2022), with representative items including "Using GAI can improve my work efficiency" and "The operational steps of GAI tools are clear and easy to understand," respectively. The self-efficacy subscale was adapted from scales designed by Bai et al. (2024) and Garcia (2023), featuring items such as "Even if no one is around to help me, I can use GAI technology in my teaching activities."

The distribution of question types is presented in Table 2, and the specific items can be found in Appendix 1.

Table 2
Distribution of survey items

Sub-questionnaire	Item number	Number of items
Demographic Characteristics	1,2,3	3
Perceived ease of use	4,5,6	3
Perceived usefulness	7,8,9	3
TPACK	10,11,12,13,14	5
Self-efficacy	15,16,17	3
Behavioral intention	18,19,20,21	4

Scale Reliability

Cronbach's alpha reliability coefficient was first used to evaluate the scale's reliability following the collection of formal data from 561 participants. The findings are presented in Table 3:

Table 3
Reliability

Variables	CITC (total correlation coefficient)	Cronbach's α
TPACK	0.849	0.954
	0.918	
	0.895	
	0.829	
	0.866	
Self-efficacy	0.815	0.913
	0.849	
	0.812	
Perceived ease of use	0.572	0.756
	0.465	
	0.742	
Perceived usefulness	0.874	0.942
	0.908	
	0.855	
Behavioral intention	0.827	0.93
	0.887	
	0.834	
	0.808	

The results showed that the reliability coefficients of all TPACK, SE, PU, and BI to use subscales exceeded 0.8, indicating good reliability, while the PE subscale exceeded 0.7, indicating acceptable reliability.

Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was used to assess model fit. CFA relies on a variety of metrics, including Chi-square to degrees of freedom ratio (CMIN/DF), Root Mean Square Error of Approximation (RMSEA), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI) to assess model fit. As shown in

Table 4, all metrics met the measurement criteria, indicating that the model had an acceptable fit.

Table 4
Model Fit

Indicators	Reference standard	Measurement value
CMIN/DF	<3	2.918
RMSEA	<0.08	0.059
IFI	>0.9	0.977
TLI	>0.9	0.971
CFI	>0.9	0.977
GFI	>0.9	0.935
AGFI	>0.9	0.909

Combined Validity and Convergent Validity

Convergent validity (Average Variance Extraction, AVE) and composite reliability (CR) were comprehensively assessed to ensure a good model fit, as shown in Table 5. The assessment process consisted of building a CFA model to compute the standardized factor loadings for each item on its dimension. Convergent validity and composite reliability values were calculated for each dimension using the AVE and CR formulas. It is important to note that the criteria for ensuring good convergence and reliable modeling are AVE values greater than or equal to 0.5 and CR values greater than or equal to 0.7 (Hair et al., 2020). Therefore, the questionnaire developed in this study showed robust convergent validity and composite reliability based on these established criteria.

Table 5
Composite reliability and convergent validity

Path			Unstd.	S.E.	P	Std.	AVE	CR
TPACK1	<---	TPACK	1			0.947	0.808	0.9546
TPACK2	<---	TPACK	0.94	0.025	***	0.891		
TPACK3	<---	TPACK	0.936	0.029	***	0.848		
TPACK4	<---	TPACK	0.978	0.022	***	0.929		
TPACK5	<---	TPACK	0.898	0.025	***	0.876		
SE1	<---	SE	1			0.947	0.7422	0.8957
SE2	<---	SE	0.895	0.037	***	0.79		
SE3	<---	SE	0.905	0.033	***	0.84		
PE1	<---	PE	1			0.855	0.5179	0.7489
PE2	<---	PE	0.523	0.056	***	0.416		
PE3	<---	PE	0.916	0.043	***	0.806		
PU1	<---	PU	1			0.941	0.8478	0.9435
PU2	<---	PU	0.995	0.027	***	0.908		
PU3	<---	PU	0.956	0.024	***	0.913		
BI1	<---	BI	1			0.943	0.7556	0.9248
BI2	<---	BI	0.982	0.026	***	0.913		
BI3	<---	BI	0.812	0.028	***	0.821		
BI4	<---	BI	0.736	0.028	***	0.791		

Distinguishing Validity

In this study, confirmatory factor analysis was performed with Amos 24.0 to assess and compare the fit of various models: the five-factor (original), four-factor, three-factor, two-factor, and one-factor models. As can be seen in Table 6, the five-factor model has the best fit of RMSEA, GFI, CFI, and other fitting indexes compared to the other models and passed the significance test of 0.001, thus indicating that the original model has a good discriminant validity.

Table 6
Discriminant validity

Distinguished Validity Results						
No.	①	②	③	④	⑤	⑥
Measurement Model and Indicator	Five-factor model	Four-factor model 1	Four-factor model 2	Three-Factor Model	Two-factor model	One-way model
χ^2	549.496	999.780	791.706	1194.930	2397.089	2469.112
df	125.000	129.000	129.000	132.000	134.000	135.000
χ^2/df	4.396	7.750	6.137	9.053	17.889	25.697
RMSEA	0.078	0.110	0.096	0.120	0.174	0.210
TLI	0.949	0.899	0.923	0.880	0.748	0.631
CFI	0.959	0.915	0.935	0.896	0.779	0.675
Model Comparison		② vs ①	③ vs ①	④ vs ①	⑤ vs ①	⑥ vs ①
$\triangle\chi^2$		450.284***	242.21***	645.434***	1847.593***	1919.616***
$\triangle$df		4.000	4.000	7.000	9.000	10.000

Note: *** indicates p<0.001
Five-factor model: TPACK，SE，PE，PU，BI
Four-factor model 1: TPACK + SE，PE，PU，BI
Four-factor model 2:TPACK，SE，PE + PU，BI
Three-factor model: TPACK + SE，PE + PU，BI
Two-factor model: TPACK + SE + PE + PU，BI
One-way model: TPACK + SE + PE + PU + BI

After confirming that the measurement model met the criteria requirements, the study continued with the path analysis of the structural model. This study examined the relationship between TPACK, PU, PE, SE, and BI among K12 teachers. In addition, this study examined the mediating effects of PU, PE, and SE on BI between TPACK and elementary and middle school teachers. To measure these mediating effects, the PROCESS add-in for SPSS was used. Through these analytical techniques, the study aimed to reveal the direct and indirect effects of TPACK, PU, PE, and SE on BI.

FINDINGS

Descriptive Statistics and Normality Test

Descriptive statistics and normality tests were conducted, and the findings are detailed in Table 7.The descriptive statistics analysis showed that the mean scores for all variables were within the range of 3-4. Considering the positively oriented scoring methodology of the questionnaire, from 1 to 5, we inferred that the participants demonstrated moderate to above-average understanding and behavior in the measured constructs.

The BI had the highest mean score of 4.1007, followed by PU and TPACK with 3.9542 and 3.7323 respectively. This suggests that the majority of primary and secondary school teachers acknowledge the significance of GAI techniques and show a strong inclination to incorporate them into their teaching methods.

Skewness and kurtosis tests were utilized to evaluate the normality of each item. Following Kline (1998) guidelines, data is deemed approximately normally distributed if the absolute skewness is below 3 and the absolute kurtosis is below 8. As shown in Table 7, the absolute values of skewness and kurtosis for all items fall within the acceptable range. Consequently, it is concluded that the data for each measured item roughly meet the normality assumption.

Table 7
Descriptive statistics and results of normality test

Variables	Items	M	SD	Skewness	Kurtosis	M	SD
TPACK	TPACK1	3.76	0.952	-0.423	-0.228	3.7323	0.903
	TPACK2	3.71	0.981	-0.448	-0.216		
	TPACK3	3.73	0.978	-0.433	-0.162		
	TPACK4	3.62	1.025	-0.387	-0.331		
	TPACK5	3.85	0.979	-0.72	0.336		
SE	SE1	3.46	1.008	-0.178	-0.32	3.4189	0.95981
	SE2	3.44	1.028	-0.229	-0.311		
	SE3	3.36	1.083	-0.271	-0.386		
PE	PE1	3.72	1.048	-0.449	-0.401	3.4581	0.87348
	PE2	3.2	1.127	-0.169	-0.554		
	PE3	3.45	1.018	-0.111	-0.456		
PU	PU1	4.02	0.973	-0.686	-0.122	3.9542	0.9399
	PU2	3.94	0.988	-0.578	-0.264		
	PU3	3.9	1.019	-0.568	-0.311		
BI	BI1	4.03	0.95	-0.696	-0.142	4.1007	0.81633
	BI2	4.03	0.938	-0.783	0.234		
	BI3	4.12	0.874	-0.737	0.075		
	BI4	4.23	0.822	-0.905	0.652		

Abbreviations: M, mean; SD, standard deviation.

Path Analysis Results

Table 8
SEM path relationship test

Path			Estimate	S.E.	C.R.(t-value)	P
PE1	<---	SE1	0.447	0.072	5.836	***
PE1	<---	TPACK1	0.359	0.08	4.827	***
PU1	<---	SE1	-0.335	0.07	-4.443	***
PU1	<---	TPACK1	0.387	0.072	5.725	***
PU1	<---	PE1	0.786	0.071	10.935	***
BI1	<---	TPACK1	0.259	0.073	3.673	***
BI1	<---	PU1	0.538	0.074	7.129	***
BI1	<---	SE1	-0.155	0.071	-1.974	*
BI1	<---	PE1	0.173	0.093	1.805	0.071

****p<0.001; **p<0.01; *p<0.05.*

The hypothesized path model was tested, and the results are presented in Table 8. The findings indicate that:

- SE significantly and positively predicted PE ($\beta = 0.447$, $p < .001$, SE = 0.072).
- TPACK significantly and positively predicted PE ($\beta = 0.359$, $p < .001$, SE = 0.080).
- SE significantly and negatively predicted PU ($\beta = -0.335$, $p < .001$, SE = 0.070). A possible explanation for this is that teachers with high self-efficacy may hold a more cautious and critical stance towards whether GAI can integrate into their established teaching practices, thereby lowering their evaluation of its usefulness.
- TPACK significantly and positively predicted PU ($\beta = 0.387$, $p < .001$, SE = 0.072).
- PE significantly and positively predicted PU ($\beta = 0.786$, $p < .001$, SE = 0.071).
- TPACK positively predicted BI ($\beta = 0.259$, $p < .001$, SE = 0.073), consistent with Hypothesis 2.
- PU positively predicted BI ($\beta = 0.538$, $p < .001$, SE = 0.074).
- SE significantly and negatively predicted BI ($\beta = -0.155$, $p < .05$, SE = 0.071), consistent with Hypothesis 1.
- No direct correlation was found between PE and BI ($p = .071$, $> .05$). Given that PE had a significant positive effect on PU, and PU in turn had a significant positive effect on BI, the total effect of PE on BI is likely composed primarily of its indirect effect through PU.

The structural model is illustrated in Figure 3.

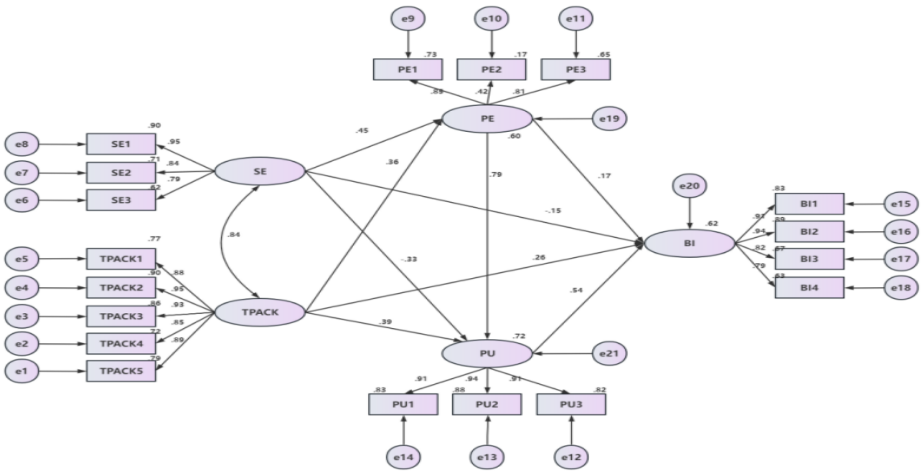

Figure 3
Results of path analysis

Mediating Effects

The Mediating Role of PE between SE and BI

Process distribution regression was employed to evaluate the mediating effect of PE between SE and BI, with results presented in Table 9. At the outset, a significant association was observed between SE and BI ($\beta=0.3943$, $p<0.01$), suggesting a total effect. In subsequent analyses, a significant link was identified between SE and the mediator PE (β=0.5746, p<0.01). The direct effect of SE on BI was significant (β=0.1569, p<0.01), as was the effect of PE on BI (β=0.4131, p<0.01), confirming PE's partial mediating role in the model, aligning with Hypothesis 4.

Table 9
Mediation of PE in SE-BI via Process Regression

Step	Dependent variable	Independent variable	*R*	R^2	*F*	*β*	*t*
1	BI	SE	0.4636	0.2149	153.0333	0.3943	12.3707
2	PE	SE	0.6314	0.3987	370.6725	0.5746	19.2529
3	BI	SE PE	0.5766	0.3324	138.9353	0.1569 0.4131	4.1353 9.9107

Based on the effect values from Table 9, the indirect effect conveyed through PE was further quantified for its magnitude and reliability using the Bootstrap method. As shown in Table 10, the calculated indirect effect value is 0.2374, with a 95% confidence interval of [0.1870, 0.2901]. The fact that this confidence interval does not include 0 again confirms the existence of the mediating role of PE in the model. From the calculation results of the relative effect size, it can be seen that PE accounts for 60.21% of the total effect. This result means that in the GAI adoption process, teachers' self-efficacy exerts over sixty percent of its influence indirectly by affecting their judgment of the technology's ease of use, highlighting the importance of lowering the technical usability barrier during the initial promotion stage.

Table 10
Mediation effect test of bootstrap analysis

Type of effect	Effect size	LLCI	ULCI	Relative effect size
Total effect	0.3943	0.3317	0.4569	1
Direct effect	0.1569	0.0824	0.2314	39.79%
Indirect effect	0.2374	0.1870	0.2901	60.21%

Mediating Role of PU between SE and BI

To examine whether self-efficacy influences usage intention through perceived usefulness, an analysis of the mediating path of PU was conducted. The mediating effect of PU between SE and BI was tested using PROCESS macro regression analysis. The results are presented in Table 11. In the initial stage of the test, a significant correlation was found between the independent variable SE and the dependent variable BI (β = 0.3943, p < 0.01), indicating the presence of a total effect. In the subsequent analysis, a significant correlation was observed between the independent variable SE and the mediating variable PU (β = 0.5173, p < 0.01). The independent variable had a significant effect on the dependent variable (β = 0.0943, p < 0.01), and PU also had a significant effect on BI (β = 0.5800, p < 0.01). This demonstrates that the mediating role of PU in the model is established, functioning as a partial mediator, which is consistent with Hypothesis 5.

Table 11
Mediation of PU in SE-BI via Process Regression.

Step	Dependent variable	Independent variable	R	R^2	F	β	t
1	BI	SE	0.4636	0.2149	153.0333	0.3943	12.3707
2	PU	SE	0.5282	0.2790	216.357	0.5173	14.7089
3	BI	SE PU	0.7324	0.5364	322.8305	0.0943 0.5800	3.2657 19.6714

To further assess the practical impact of this pathway, we calculated the specific value of the mediating effect of PU. As shown in Table 12, the calculated indirect effect value is 0.3000, with a 95% confidence interval of [0.2491, 0.3555]. The fact that this confidence interval does not include 0 further confirms the existence of the mediating role of PU in the model. From the results of the relative effect size calculation, it can be seen that PU accounts for 76.08% of the total effect. This indicates that the vast majority (over three-quarters) of teachers' sense of efficacy drives their intention to use GAI by enhancing their belief in its "instructional usefulness."

Table 12
Mediation effect test of bootstrap analysis

Type of effect	Effect size	LLCI	ULCI	Relative effect size
Total effect	0.3943	0.3317	0.4569	1
Direct effect	0.0943	0.0376	0.1510	23.92%
Indirect effect	0.3000	0.2491	0.3555	76.08%

Mediating Role of PU between TPACK and BI

To examine whether TPACK promotes behavioral intention through perceived usefulness, an analysis was conducted on the mediating role of PU. The results are presented in Table 13. In the initial stage of the test, a significant correlation was found between the independent variable TPACK and the dependent variable BI ($\beta = 0.5403$, $p < 0.01$), indicating the presence of a total effect. In the subsequent test, a significant correlation was observed between the independent variable TPACK and the mediating variable PU ($\beta = 0.6831$, $p < 0.01$). The independent variable had a significant effect on the dependent variable ($\beta = 0.1922$, $p < 0.01$), and PU also had a significant effect on BI ($\beta = 0.5097$, $p < 0.01$). This indicates that the mediating role of PU in the model is established, functioning as a partial mediator, which is consistent with Hypothesis 3.

Table 13
Mediation of PU in TPACK-BI via Process Regression

Step	Dependent variable	Independent variable	R	R^2	F	β	t
1	BI	TPACK	0.5977	0.3572	310.6748	0.5403	17.6260
2	PU	TPACK	0.6563	0.4307	422.9397	0.6831	20.5655
3	BI	TPACK PU	0.7438	0.5533	345.5446	0.1922 0.5097	5.6881 15.6485

Subsequently, the effect size of this mediating pathway was quantified. As shown in Table 14, the calculated indirect effect value is 0.3482, with a 95% confidence interval of [0.2893, 0.4063]. The fact that this confidence interval does not include 0 further confirms the existence of the mediating role of PU in the model. From the results of the relative effect size calculation, it can be seen that PU accounts for 66.30% of the total effect. This indicates that over 60% of the effect of teachers' professional TPACK knowledge on their behavioral intention needs to be realized by being transformed into a firm belief in the usefulness of GAI tools.

Table 14
Mediation effect test of bootstrap analysis.

Type of effect	Effect size	LLCI	ULCI	Relative effect size
Total effect	0.5403	0.4801	0.6005	1
Direct effect	0.1922	0.1256	0.2587	35.57%
Indirect effect	0.3482	0.2893	0.4063	66.30%

Mediating Role of PE between TPACK and BI

Table 15 presents the mediation analysis results for PE's role between TPACK and BI. The initial phase of the analysis uncovered a substantial correlation between TPACK and BI (β=0.5403, $p<0.01$), indicating a total effect. A subsequent test affirmed a significant correlation between TPACK and the mediator PE (β=0.5731, $p<0.01$). The direct effect of TPACK on BI was significant (β=0.3716, $p<0.01$), and PE's influence on BI was also significant (β=0.2944, $p<0.01$), suggesting that PE partially mediates the relationship between TPACK and BI, aligning with Hypothesis 7.

Table 15
Mediation of PE in TPACK-BI via Process Regression

Step	Dependent variable	Independent variable	R	R^2	F	β	t
1	BI	TPACK	0.5977	0.3572	310.6748	0.5403	17.6260
2	PE	TPACK	0.5924	0.3510	302.2804	0.5731	17.3862
3	BI	TPACK PE	0.6493	0.4216	203.3996	0.3716 0.2944	10.2863 7.8831

Similarly, the mediating effect value of this pathway was quantitatively estimated. As shown in Table 16, the calculated indirect effect value is 0.1678, with a 95% confidence interval of [0.1207, 0.2184]. The fact that this confidence interval does not include 0 again confirms the existence of the mediating role of PE in the model. From the results of the relative effect size calculation, it can be seen that PE accounts for 31.06% of the total effect. This indicates that nearly seventy percent of the influence of teachers' TPACK knowledge on their behavioral intention is realized by enhancing their perception of the ease of use of GAI tools. Together with the mediating pathway of PU, this finding illustrates that professional knowledge drives technology adoption through a dual mechanism: both perceived usefulness and perceived ease of use.

Table 16
Mediation effect test of bootstrap analysis

Type of effect	Effect size	LLCI	ULCI	Relative effect size
Total effect	0.5403	0.4801	0.6005	1
Direct effect	0.3716	0.3006	0.4426	68.78%
Indirect effect	0.1678	0.1207	0.2184	31.06%

Mediating Role of PE and PU between SE and BI

The effects of PE and PU as chained mediating variables on the relationship between TPACK and BI were investigated. The confidence interval for the total effect [0.3317,0.4569] did not include 0, confirming the significance of the effect of TPACK on BI, with a β-value of 0.3943. The confidence interval for the direct effect [0.0006,0.1256] also excluded 0, indicating that the direct effect was significant. In addition, the confidence interval [0.2739,0.3913] for the total indirect effect did not include 0. The total indirect effect accounted for 83.87% of the total effect. The total indirect effect of teachers' self-efficacy, PE, and PU on teachers' BI was stronger than the direct effect, indicating that PE and PU were significant mediating variables in influencing teachers' behavioral intention, consistent with Hypothesis 6. The total indirect effect was distributed across three paths, with p-values of the indirect effect for all three paths being less than 0.001 and the confidence intervals of the paths not being 0 (Table 15), which demonstrated that all three mediating effect paths were supported in the effect of SE on BI. Specifically, path 3 (TPACK -> PE -> PU > BI) had the largest indirect effect, suggesting that the combined effect of teachers' PE and PU was more significant.

Table 17
Chain mediation effect of PE and PU between SE and BI.

Path	β	se	Bootstrap 95% CI	
			Lower	Upper
Total effect	0.3943	0.0319	0.3317	0.4569
Direct effect	0.0636	0.0321	0.0006	0.1256
Indirect effect	0.3307	0.0298	0.2739	0.3913
Path 1	0.0503	0.0251	0.0011	0.1016
Path 2	0.0933	0.0234	0.0481	0.1406
Path 3	0.1871	0.0225	0.1443	0.2322

Abbreviations: Path 1, SE → PE → BI; Path 2, SE → PU → BI; Path 3, SE → PE → PU → BI; se, standard error.

DISCUSSION AND CONCLUSION

Based on the Technology Acceptance Model, this study explored the relationships among K-12 teachers' TPACK, self-efficacy, and their behavioral intention to use GAI for instructional assistance. Given that GAI's dialog-based "generative" nature and the uncertainty of its outputs significantly distinguish it from traditional educational technologies, it may reshape teachers' technology acceptance process. Therefore, this study employed structural equation modeling to empirically examine the interrelationships among TPACK, self-efficacy, perceived ease of use, perceived usefulness, and behavioral intention within the specific technological context of GAI.

First, TPACK and self-efficacy demonstrated a direct positive influence on teachers' behavioral intention to use GAI. This indicates that in the context of GAI, both factors remain crucial foundations driving adoption intention, which aligns with findings from most studies on traditional technologies (Teo et al., 2019; Al Darayseh, 2023; Bai et al., 2020). However, inconsistencies with some research (Usman et al., 2019) also suggest that this relationship may be moderated by the type of technology and contextual factors. The characteristics of GAI may activate or alter the specific pathways and conditions through which TPACK and self-efficacy exert their influence, urging us not to simply apply past conclusions. Instead, it is necessary to further investigate through the subsequent findings of this study the more refined mediating mechanisms through which these factors ultimately influence behavioral intention.

Second, the study found that teachers' perceived ease of use of GAI technology mediates the influence of self-efficacy on behavioral intention (SE → PE → BI). This is consistent with findings in other technological contexts (Khlaisang et al., 2023; Huang et al., 2022; Usman et al., 2020), suggesting that even when facing a new technology like GAI, the classic socio-cognitive pathway—where confidence enhances perceived ease of use, which in turn promotes willingness to use—remains valid. However, the greater significance of this finding lies in revealing one fundamental, but not exclusive, pathway through which self-efficacy operates. It implies that teachers' confidence first promotes adoption by lowering their psychological anticipation of the operational difficulty of the technology, thereby laying the groundwork for subsequent exploration of chain mediation effects.

Third, the study further revealed the complete mediating chain through which self-efficacy influences behavioral intention (SE → PE → PU → BI). This aligns with some research models in the field of technology acceptance (Rivers, 2021), indicating that confidence first reduces the perceived difficulty of using the technology, and this perception of ease further strengthens the belief in the technology's value output, which is then ultimately translated into the intention to use. However, a significant negative direct relationship was found between self-efficacy and perceived usefulness. This contrasts with the conclusions of some studies (Thongsri et al., 2020), revealing a paradox between teachers' technological confidence and their value judgments in the context of GAI. A possible explanation for this is that there remains a significant gap between the core functions of current tools (such as content generation and instant feedback) and the most complex, core teaching challenges teachers face (e.g., cultivating students' higher-order thinking skills, providing deeply personalized feedback) (Abdelghani et al., 2023). This phenomenon can be understood through the theoretical lens of "expert-novice differences." For teachers with strong professional confidence, the decision to adopt GAI shifts from a simple, linear process of "ease of use to usefulness" to a critical "value re-evaluation" process based on professional cognition (Bransford et al., 2000).

Fourth, the study found that TPACK can produce mediating effects on BI through both PU and PE (TPACK → PU → BI and TPACK → PE → BI). This is consistent with most research conclusions (Yang et al., 2021; Hsu, 2016), meaning that teachers' integrated professional knowledge (TPACK) plays a more central and active role as a cognitive hub in GAI adoption. It is not merely a static reservoir of ability but an active interpretive framework: teachers with richer professional knowledge are better able to deeply understand the pedagogical potential of GAI (thus enhancing PU) and to master its operation (thus enhancing PE), making them more willing to use it. This highlights the crucial role of TPACK in both lowering the cognitive threshold of technology and uncovering its value.

Finally, no direct association was found between perceived ease of use (PE) and behavioral intention (BI). This contradicts some studies (Usman et al., 2020; Hong et al., 2021) but aligns with the core logic of the Technology Acceptance Model, which posits that ease of use indirectly influences usage intention through usefulness (Igbaria & Iivari, 1995). This implies that when evaluating GAI, "whether it is easy to use" is no longer sufficient to directly drive teachers' adoption willingness. Instead, ease of use is translated into usage behavior (PE → PU → BI) only when it helps demonstrate that the tool can deliver substantial pedagogical value (i.e., enhances perceived usefulness, PU). This reflects the fundamental distinction between GAI as a high-involvement tool and simpler tools: when faced with complex teaching tools, teachers are more inclined to engage in rational cost-benefit analysis. As long as the perceived pedagogical benefit (usefulness) is sufficiently great, they are willing to tolerate a certain degree of operational difficulty. Therefore, the lack of a direct link between PE and BI precisely indicates that the focus of teachers' decision-making has shifted from "whether using it saves effort" to the more mature value consideration of "whether using it is worthwhile."

In summary, this study reveals the complexity of K-12 teachers' technology acceptance mechanisms in the context of the emerging technology of Generative Artificial Intelligence. The core finding indicates that teachers' TPACK and self-efficacy are the key intrinsic factors driving usage. At the theoretical level, the study uncovers the specificity of applying the Technology Acceptance Model to GAI: the negative influence of self-efficacy on perceived usefulness, coupled with the indirect effect of perceived ease of use on behavioral intention, jointly illustrates that for teachers, the ease of use of GAI is no longer the primary barrier; rather, its usefulness is the core consideration. Furthermore, this evaluative standard varies with the level of teachers' professional expertise. This deepens our understanding of the contextualized interaction among "human-technology-practice" in technology acceptance.

At the practical level, the findings of this study provide clear directions for teacher training and policy formulation: teacher training should shift from basic operations to focusing on how to leverage GAI to solve real teaching challenges in the classroom, thereby tangibly enhancing teachers' perceived usefulness of the technology. For experienced, highly efficacious teachers, support should be provided that emphasizes high-level integration and innovative demonstration, proving the technology's value in enhancing their professional practice. Simultaneously, tool development and promotion should aim to bridge the gap between existing functionalities and core teaching challenges, advocating for the development of scenario-specific and subject-specialized tools that can directly support complex instructional decision-making.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Although this study provides valuable empirical support for understanding K-12 teachers' behavioral intention to use generative artificial intelligence in teaching, several limitations remain that should be addressed and expanded upon in future research.

Methodologically, the study relies on cross-sectional survey data. While self-reported measures allow for efficient data collection from a broad sample, they are still susceptible to social desirability bias and cannot fully capture the dynamic decision-making processes involved when teachers integrate technology into authentic classroom contexts. In terms of scope, the sample is primarily drawn from specific regions within China, which calls for caution when generalizing the findings to educational settings with different cultural, policy, and economic backgrounds. Regarding variable design, the current model does not incorporate contextual factors such as school-level technological infrastructure, organizational support, or collegial collaboration climate, all of which may play significant moderating roles in teachers' technology adoption processes.

Based on these limitations, future research directions can be more targeted. Methodologically, longitudinal tracking designs or quasi-experimental studies may be adopted to more rigorously examine causal relationships between variables and their dynamic evolution mechanisms. In terms of research scope, cross-regional and cross-cultural comparative studies could be conducted to test the contextual boundaries and generalizability of the current theoretical model. To deepen the research, it is recommended to incorporate qualitative methods (such as in-depth interviews, classroom observations, and case studies) to uncover the specific mechanisms and individual experiential narratives behind quantitative findings. For further expansion, subsequent work should focus on examining the moderating effects of environmental variables. Through methods such as hierarchical regression or multi-group analysis, future studies can systematically address "under what conditions" the core mechanisms are strengthened or weakened, thereby constructing a theoretical model with greater explanatory power and contextual adaptability.

ACKNOWLEDGMENTS

2025 Major Project of Philosophy and Social Sciences Research in Henan Provincial Colleges and Universities: "The Formation Mechanism and Governance Path of Primary and Secondary School Teachers' Digital-Intelligent Burden" (Project No.: 2025-JCZD-08).

2025 Henan Provincial Philosophy and Social Sciences Project for Strengthening the Province through Education: "Construction of a Multimodal Assessment Model for Learners' Critical Thinking in Real Classroom Scenarios" (Project No.: 2025JYQS0222).

2025 Key Scientific Research Project Plan of Henan Provincial Institutions of Higher Education: "Cognitive Diagnosis and Intervention of Online Learning Based on Intelligent Teaching Agents" (Project No.: 25B880002).

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